a-task1-titanic-classification

August 12, 2024

CodeAlpha - Task1 - Titanic Classification

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix
```

[2]:
```
# Load the dataset
ds = pd.read_csv("titanic.csv")

# Display the first few rows of the dataset
print(ds.head())
```

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
```

```
3      0             113803   53.1000   C123         S
4      0             373450    8.0500    NaN         S
```

Data Preprocessing

[6]:
```python
ds.columns
```

[6]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch',
       'Fare', 'Embarked'],
      dtype='object')
```

[8]:
```python
for i in ds.columns:
    if ds[f"{i}"].sum()==0:
        ds.drop(f"{i}", axis=1, inplace=True)
ds.head()
```

[8]:

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	0	3	0	22.0	1	0	7.2500	0
1	2	1	1	1	38.0	1	0	71.2833	1
2	3	1	3	1	26.0	0	0	7.9250	0
3	4	1	1	1	35.0	1	0	53.1000	0
4	5	0	3	0	35.0	0	0	8.0500	0

[9]:
```python
ds.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Sex          891 non-null    int64
 4   Age          891 non-null    float64
 5   SibSp        891 non-null    int64
 6   Parch        891 non-null    int64
 7   Fare         891 non-null    float64
 8   Embarked     891 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 62.8 KB
```

[10]:
```python
ds.describe()
```

[10]:
```
       PassengerId    Survived      Pclass         Sex         Age  \
count   891.000000  891.000000  891.000000  891.000000  891.000000
mean    446.000000    0.383838    2.308642    0.352413   29.361582
std     257.353842    0.486592    0.836071    0.477990   13.019697
```

```
min       1.000000    0.000000    1.000000    0.000000    0.420000
25%     223.500000    0.000000    2.000000    0.000000   22.000000
50%     446.000000    0.000000    3.000000    0.000000   28.000000
75%     668.500000    1.000000    3.000000    1.000000   35.000000
max     891.000000    1.000000    3.000000    1.000000   80.000000

            SibSp       Parch        Fare    Embarked
count  891.000000  891.000000  891.000000  891.000000
mean     0.523008    0.381594   32.204208    0.361392
std      1.102743    0.806057   49.693429    0.635673
min      0.000000    0.000000    0.000000    0.000000
25%      0.000000    0.000000    7.910400    0.000000
50%      0.000000    0.000000   14.454200    0.000000
75%      1.000000    0.000000   31.000000    1.000000
max      8.000000    6.000000  512.329200    2.000000
```

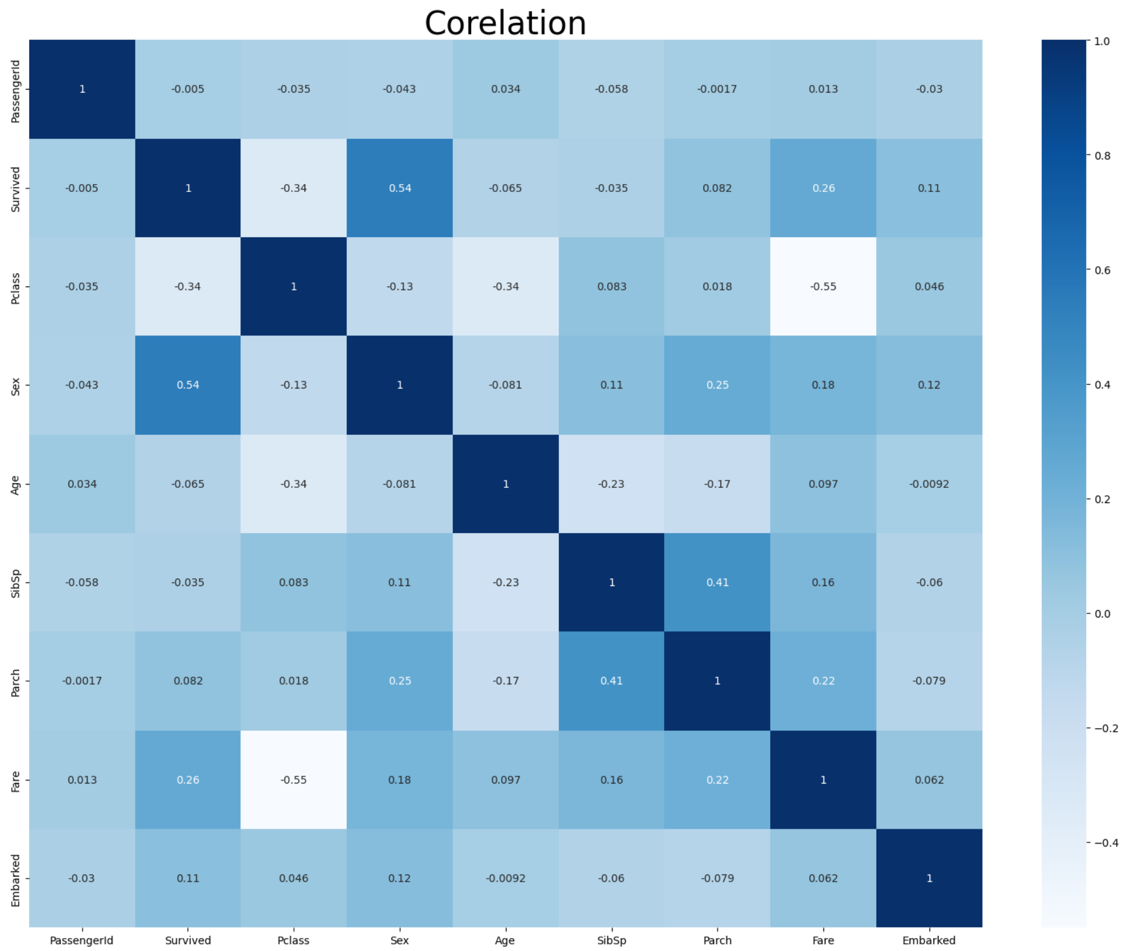
[11]:
```python
ds.isnull().sum()
```

[11]:
```
PassengerId    0
Survived       0
Pclass         0
Sex            0
Age            0
SibSp          0
Parch          0
Fare           0
Embarked       0
dtype: int64
```

[12]:
```python
ds.fillna(ds.Embarked.mean(), inplace = True)
ds.isnull().sum()
```

[12]:
```
PassengerId    0
Survived       0
Pclass         0
Sex            0
Age            0
SibSp          0
Parch          0
Fare           0
Embarked       0
dtype: int64
```

[13]:
```python
plt.figure(figsize=(20, 15))
sns.heatmap(ds.corr(), annot=True, cmap='Blues')
plt.title("Corelation", size=30)
plt.show()
```



[14]:
```python
ds.head()
```

[14]:

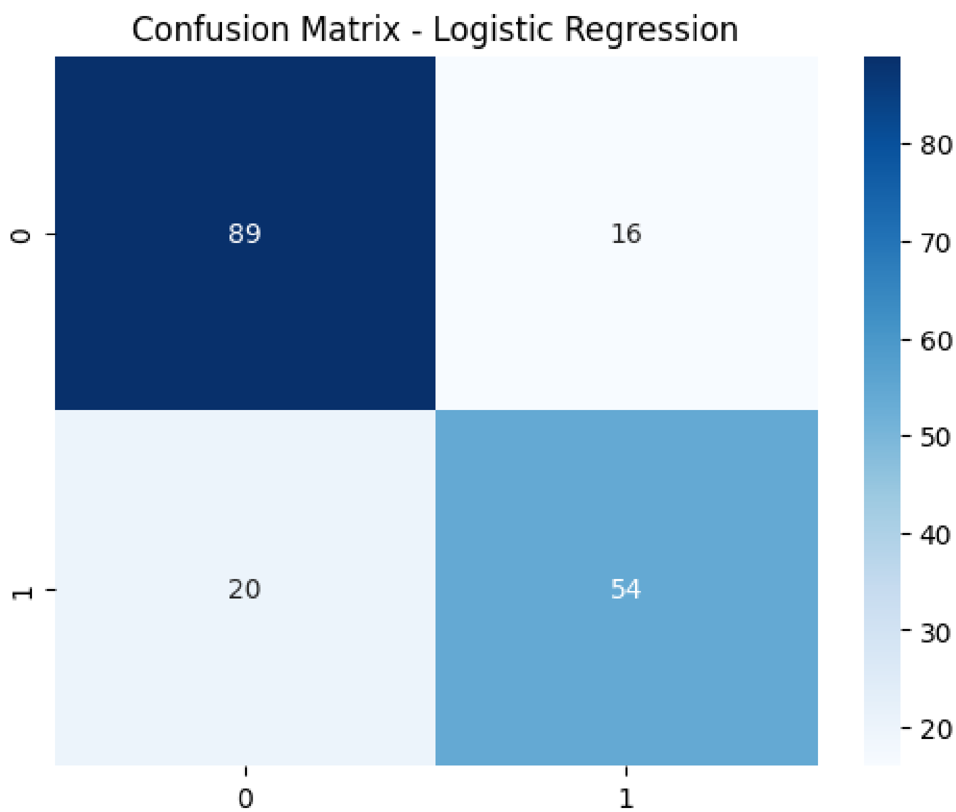
	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	0	3	0	22.0	1	0	7.2500	0
1	2	1	1	1	38.0	1	0	71.2833	1
2	3	1	3	1	26.0	0	0	7.9250	0
3	4	1	1	1	35.0	1	0	53.1000	0
4	5	0	3	0	35.0	0	0	8.0500	0

Logistic Regression

[22]:
```python
# Logistic Regression
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
y_pred_logreg = logreg.predict(X_test)

# Evaluation
print("Logistic Regression")
```

```python
print("Accuracy:", accuracy_score(y_test, y_pred_logreg))
print(classification_report(y_test, y_pred_logreg))

# Confusion Matrix
sns.heatmap(confusion_matrix(y_test, y_pred_logreg), annot=True, fmt='d',␣
 ↪cmap='Blues')
plt.title('Confusion Matrix - Logistic Regression')
plt.show()
```

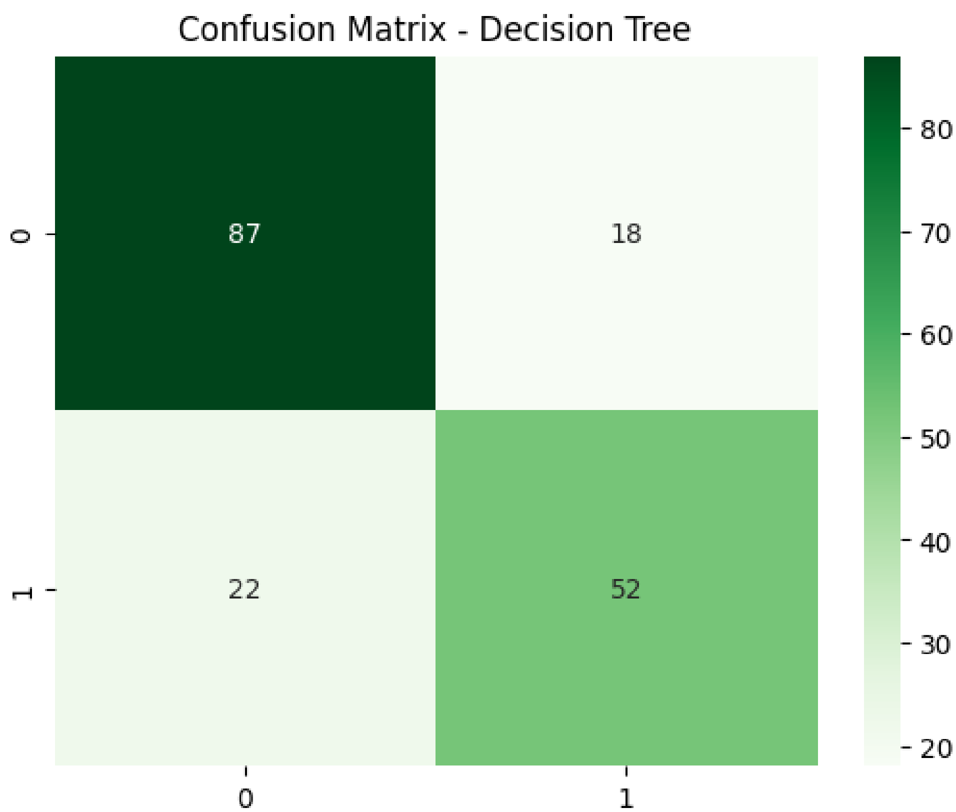
```
Logistic Regression
Accuracy: 0.7988826815642458
              precision    recall  f1-score   support

           0       0.82      0.85      0.83       105
           1       0.77      0.73      0.75        74

    accuracy                           0.80       179
   macro avg       0.79      0.79      0.79       179
weighted avg       0.80      0.80      0.80       179
```



Decision Tree

[20]:
```
# Decision Tree
dtree = DecisionTreeClassifier()
dtree.fit(X_train, y_train)
y_pred_dtree = dtree.predict(X_test)

# Evaluation
print("Decision Tree")
print("Accuracy:", accuracy_score(y_test, y_pred_dtree))
print(classification_report(y_test, y_pred_dtree))

# Confusion Matrix
sns.heatmap(confusion_matrix(y_test, y_pred_dtree), annot=True, fmt='d',␣
 ↪cmap='Greens')
plt.title('Confusion Matrix - Decision Tree')
plt.show()
```

```
Decision Tree
Accuracy: 0.776536312849162
              precision    recall  f1-score   support

           0       0.80      0.83      0.81       105
           1       0.74      0.70      0.72        74

    accuracy                           0.78       179
   macro avg       0.77      0.77      0.77       179
weighted avg       0.78      0.78      0.78       179
```

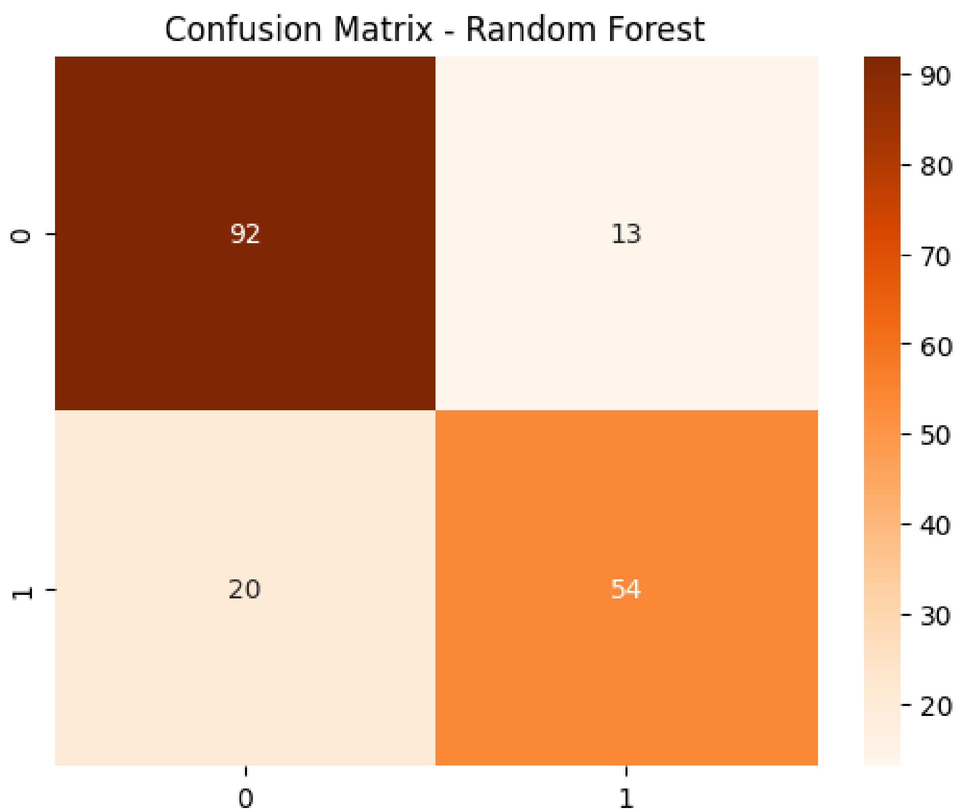


Random Forest

[23]:
```
# Random Forest
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)

# Evaluation
print("Random Forest")
print("Accuracy:", accuracy_score(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))

# Confusion Matrix
sns.heatmap(confusion_matrix(y_test, y_pred_rf), annot=True, fmt='d',␣
↪cmap='Oranges')
plt.title('Confusion Matrix - Random Forest')
plt.show()
```

```
Random Forest
Accuracy: 0.8156424581005587
              precision    recall  f1-score   support
```

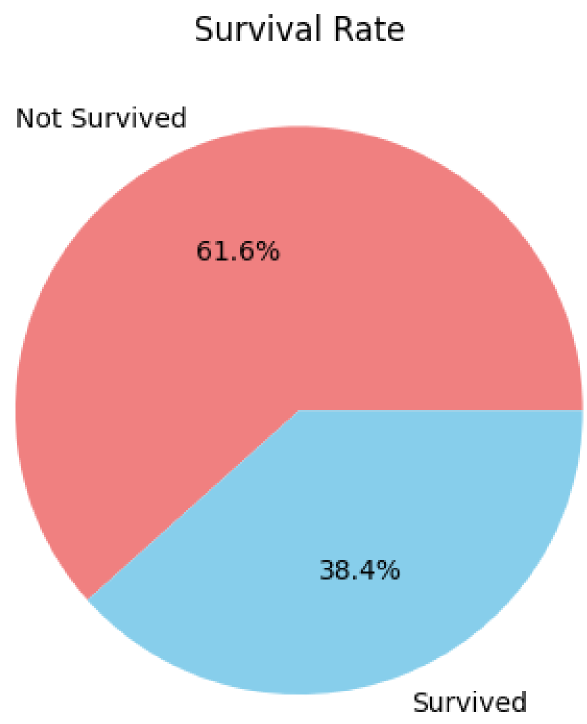
```
              0       0.82      0.88      0.85       105
              1       0.81      0.73      0.77        74

       accuracy                           0.82       179
      macro avg       0.81      0.80      0.81       179
   weighted avg       0.82      0.82      0.81       179
```



Visualization

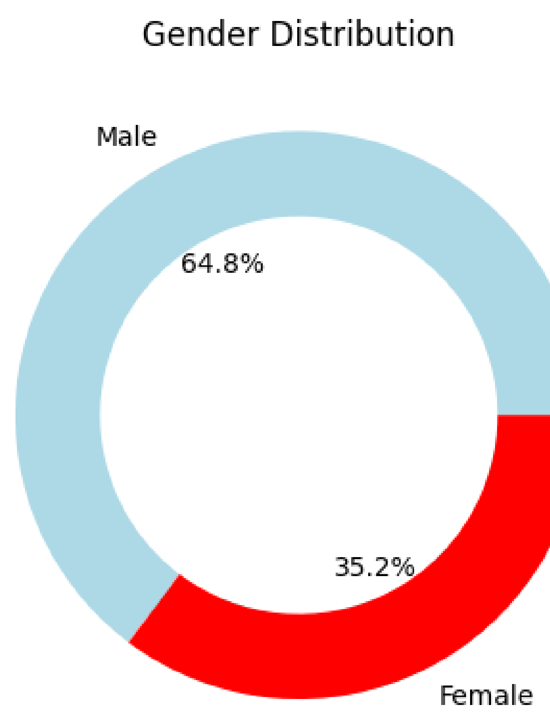
Pie Chart - Survival Rate

[25]:
```python
# Pie chart of survival rate
survived_counts = ds['Survived'].value_counts()
plt.pie(survived_counts, labels=['Not Survived', 'Survived'], autopct='%1.
↪1f%%', colors=['lightcoral', 'skyblue'])
plt.title('Survival Rate')
plt.show()
```



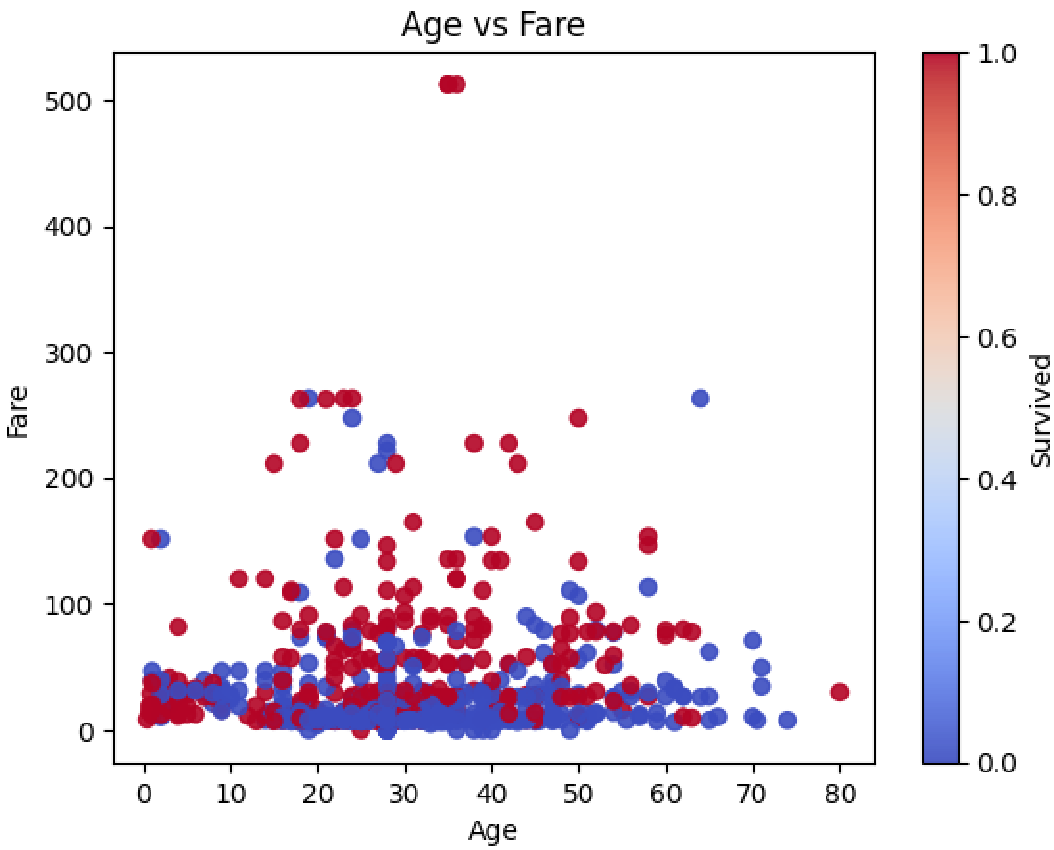
Donut Chart - Gender Distribution

[28]:
```
# Donut chart of gender distribution
gender_counts = ds['Sex'].value_counts()
plt.pie(gender_counts, labels=['Male', 'Female'], autopct='%1.1f%%',␣
 ↪colors=['lightblue', 'Red'], wedgeprops=dict(width=0.3))
plt.title('Gender Distribution')
plt.show()
```



Scatter Plot - Age vs. Fare

[30]:
```
# Scatter plot of Age vs Fare
plt.scatter(ds['Age'], ds['Fare'], c=ds['Survived'], cmap='coolwarm', alpha=0.9)
plt.title('Age vs Fare')
plt.xlabel('Age')
plt.ylabel('Fare')
plt.colorbar(label='Survived')
plt.show()
```



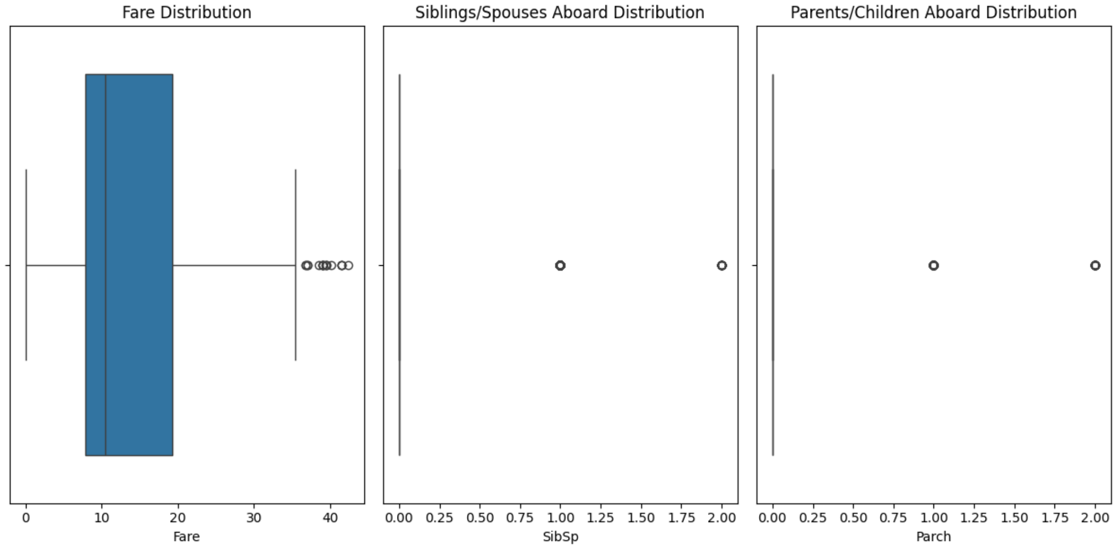
[34]:
```python
# Sample DataFrame (assuming `ds` is already defined)
# Check column names and initial rows to ensure they are correct
print("Column Names:")
print(ds.columns)
print("\nSample Data:")
print(ds.head())
```

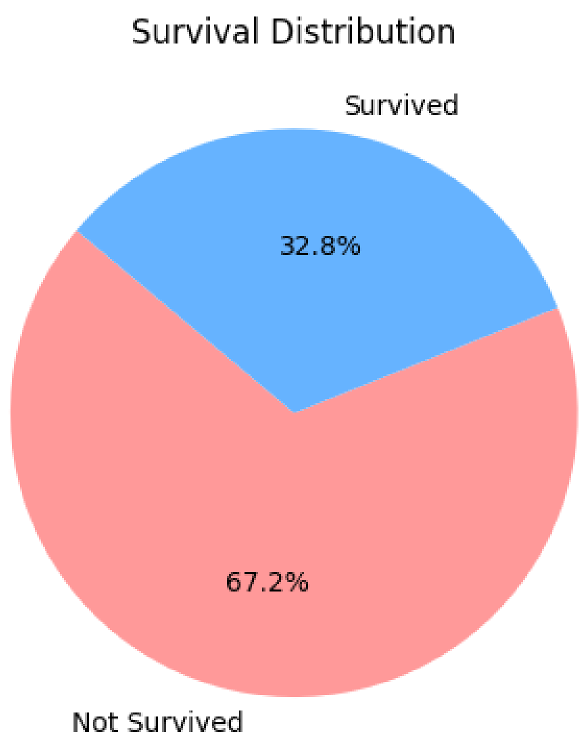
```
Column Names:
Index(['PassengerId', 'Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch',
       'Fare', 'Embarked'],
      dtype='object')

Sample Data:
   PassengerId  Survived  Pclass  Sex   Age  SibSp  Parch     Fare  Embarked
0            1         0       3    0  22.0      1      0   7.2500         0
2            3         1       3    1  26.0      0      0   7.9250         0
4            5         0       3    0  35.0      0      0   8.0500         0
5            6         0       3    0  28.0      0      0   8.4583         2
7            8         0       3    0   2.0      3      1  21.0750         0
```

[37]:
```
ds.columns
```

[37]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch',
       'Fare', 'Embarked'],
      dtype='object')
```

[38]:
```
# Dropping outliers
ds = ds[ds['Fare'] < 45]
ds = ds[ds['SibSp'] < 3]  # Changed 'sibsp' to 'SibSp'
ds = ds[ds['Parch'] < 3]

# Plot boxplots for numerical features
plt.figure(figsize=(12, 6))

# Boxplot for 'Fare'
plt.subplot(1, 3, 1)
sns.boxplot(x=ds['Fare'])
plt.title('Fare Distribution')

# Boxplot for 'SibSp'
plt.subplot(1, 3, 2)
sns.boxplot(x=ds['SibSp'])  # Changed 'sibsp' to 'SibSp'
plt.title('Siblings/Spouses Aboard Distribution')

# Boxplot for 'Parch'
plt.subplot(1, 3, 3)
sns.boxplot(x=ds['Parch'])
plt.title('Parents/Children Aboard Distribution')

plt.tight_layout()
plt.show()

# Pie chart for target variable distribution
labels = ['Not Survived', 'Survived']
sizes = ds['Survived'].value_counts()  # Assuming '2urvived' should be
 ↪'Survived'
colors = ['#ff9999', '#66b3ff']
plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%', startangle=140)
plt.title('Survival Distribution')
plt.show()
```





[39]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Assuming 'Survived' is the target variable and others are features
```

```
X = ds.drop('Survived', axis=1)
y = ds['Survived']

# Split the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Standardize features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

[40]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

# Initialize the model
model = LogisticRegression()

# Train the model
model.fit(X_train, y_train)

# Predict on the test set
y_pred = model.predict(X_test)

# Evaluate the model
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.8602941176470589
Classification Report:
               precision    recall  f1-score   support

           0       0.87      0.92      0.90        90
           1       0.83      0.74      0.78        46

    accuracy                           0.86       136
   macro avg       0.85      0.83      0.84       136
weighted avg       0.86      0.86      0.86       136
```

[41]:
```
from sklearn.tree import DecisionTreeClassifier

# Initialize the model
model = DecisionTreeClassifier()

# Train the model
model.fit(X_train, y_train)
```

```python
# Predict on the test set
y_pred = model.predict(X_test)

# Evaluate the model
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.7352941176470589
Classification Report:
               precision    recall  f1-score   support

           0       0.79      0.81      0.80        90
           1       0.61      0.59      0.60        46

    accuracy                           0.74       136
   macro avg       0.70      0.70      0.70       136
weighted avg       0.73      0.74      0.73       136
```

[42]:

```python
from sklearn.ensemble import RandomForestClassifier

# Initialize the model
model = RandomForestClassifier()

# Train the model
model.fit(X_train, y_train)

# Predict on the test set
y_pred = model.predict(X_test)

# Evaluate the model
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.8676470588235294
Classification Report:
               precision    recall  f1-score   support

           0       0.85      0.97      0.91        90
           1       0.91      0.67      0.78        46

    accuracy                           0.87       136
   macro avg       0.88      0.82      0.84       136
weighted avg       0.87      0.87      0.86       136
```

```
[ ]:
```